Abstract

Brain tumor detection through medical imaging is a critical task in the healthcare field, with significant implications for early diagnosis and treatment planning. This project presents a deep learning-based approach for binary classification of brain MRI scans into tumor and no-tumor categories. Due to the limited size and imbalance in available datasets, two public MRI datasets from Kaggle were combined and preprocessed to enhance the quality and quantity of training data. The dataset was carefully balanced through targeted data augmentation and downsampling techniques. A ResNet50-based convolutional neural network was employed for feature extraction and classification. The model achieved high accuracy and generalization capability on unseen test data. This report documents the full workflow including dataset preparation, augmentation strategies, model architecture, training procedure, evaluation metrics, and performance analysis.

1. Introduction

Brain tumors are among the most critical and life-threatening neurological disorders. Early and accurate diagnosis is essential for effective treatment planning and improved patient outcomes. Magnetic Resonance Imaging (MRI) is widely used for brain tumor detection due to its high-resolution imaging and non-invasive nature. However, analyzing MRI scans manually is time-consuming and prone to human error.

This project aims to develop an automated system for brain tumor detection using deep learning techniques. The system classifies MRI brain scans into two categories: **tumor** (yes) and **no tumor** (no). To achieve this, convolutional neural networks (CNNs), particularly the **ResNet50** architecture, were leveraged due to their proven success in image classification tasks.

Given the limited size and imbalance of publicly available MRI datasets, this project combines two Kaggle datasets and applies advanced data preprocessing, augmentation, and transfer learning techniques to build a robust binary classification model. The goal is to create an accurate and efficient diagnostic support tool that can assist radiologists in identifying brain tumors from MRI scans.

2. Problem Statement

Brain tumors pose a significant threat to human life, often requiring early and accurate diagnosis to improve the chances of successful treatment. Traditional diagnostic methods rely heavily on the manual analysis of MRI scans by medical professionals, which can be time-consuming, subjective, and prone to human error, especially when dealing with large volumes of imaging data.

The primary challenge addressed in this project is the development of an automated system capable of accurately classifying brain MRI scans into two categories: **tumor** (yes) and **no tumor** (no). This binary classification task is complicated by several key issues:

- **Limited data availability**: Publicly available datasets are often small and insufficient for training deep learning models effectively.
- **Class imbalance**: Datasets typically contain significantly more images of one class (e.g., tumor) than the other (e.g., no tumor), which can bias the model.
- **Variability in tumor types and MRI scan quality**: Differences in tumor appearance, location, and imaging protocols add complexity to the classification task.

The goal of this project is to overcome these challenges by leveraging data augmentation, dataset merging, and transfer learning using a ResNet50 architecture, ultimately creating a model that can assist healthcare professionals in the reliable and efficient detection of brain tumors from MRI scans.

3. Project Objectives

The primary objective of this project is to design and implement a deep learning-based system capable of accurately detecting brain tumors in MRI images. To achieve this, the project focuses on the following specific goals:

1. Dataset Expansion and Integration
   Combine and preprocess two publicly available brain MRI datasets to create a comprehensive and balanced dataset suitable for binary classification (tumor vs. no tumor).
2. Class Balancing
   Address the class imbalance problem through selective data augmentation for the minority class and controlled downsampling for the majority class to ensure fair model training.
3. Image Preprocessing and Standardization
   Resize and normalize all MRI images to a uniform shape and scale to meet the input requirements of modern convolutional neural networks.
4. Model Selection and Implementation
   Utilize transfer learning by implementing a ResNet50-based convolutional neural network, optimized for binary classification of medical images.
5. Model Training and Evaluation
   Train the model on the preprocessed dataset and evaluate its performance using appropriate metrics such as accuracy, precision, recall, F1-score, and confusion matrix.
6. Visualization and Reporting
   Visualize training progress, analyze results, and document all steps and findings to ensure reproducibility and clarity in model development and performance assessment.

4. Methodology

4.1 Data collection

The project utilized two publicly available MRI brain tumor datasets sourced from Kaggle:

1. **Dataset 1 – Brain MRI Images for Brain Tumor Detection**

Contains images labeled as either:

1. **Yes Tumor** – indicating the presence of a brain tumor 2.**No Tumor** – indicating no tumor present

This dataset provides a binary classification structure.

2. **Dataset 2 – Brain Tumor MRI Dataset**

Contains MRI images grouped into four classes:

1.Glioma   2. Meningioma   3.Pituitary   4.No tumor

For the purpose of binary classification, the three tumor types were merged into a single **"yes"** class, while "no tumor" was kept as **"no"**.

Both datasets were downloaded using the Kaggle API and merged into a unified format to support a binary classification model: **tumor present (yes)** vs. **no tumor (no)**.

4.2 Preprocessing

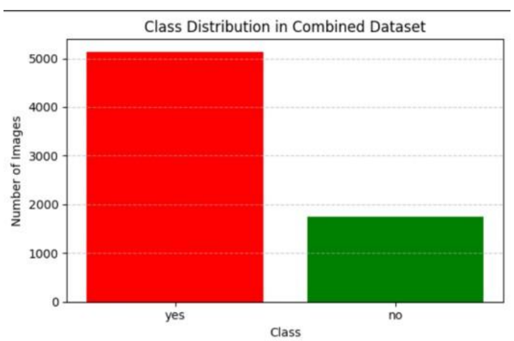
Initially, the project began with the **"Brain MRI Images for Brain Tumor Detection"** dataset. During the preprocessing phase, several crucial steps were performed:

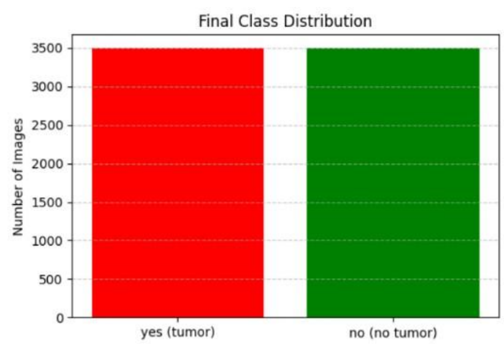
- ✓ **Duplicate and Corrupted Image Removal:**
  The dataset was scanned for duplicate and corrupted image files, which were subsequently removed to ensure data quality and avoid training bias.
- ✓ **Class Imbalance Handling (Initial Attempt):**
  The dataset was highly imbalanced, with significantly fewer images in the **"no tumor"** class. To address this, we applied data augmentation techniques such as rotation, shifting, and zooming to artificially increase the number of **"no"** images. However, this approach did not yield stable model performance — the accuracy fluctuated heavily during training, suggesting that the dataset size and quality were insufficient.

As a result, a **second dataset** (**"Brain Tumor MRI Dataset"**) was integrated to enhance the model's learning capability.

After combining both datasets:

- ✓ **Rechecking and Removing Duplicates/Corrupted Files:**
  The merged dataset was cleaned again to eliminate any remaining duplicated or unreadable images.
- ✓ **Data Augmentation:**
  Since the **"no tumor"** class remained underrepresented, additional augmentation was applied to reach **3,500** images.
- ✓ **Undersampling the Majority Class:**
  The **"tumor" (yes)** class originally had over 5,000 images. To maintain balance and avoid bias, it was randomly undersampled to also contain **3,500** images.





- ✓ **Image Resizing:**
  To ensure consistency and compatibility with deep learning models (like ResNet50), all images were resized to a fixed dimension of **224x224 pixels**.
- ✓ **Data Splitting:**
  The cleaned and balanced dataset (7,000 images total) was divided into three subsets:

  Training set – 70% of the data **Validation set** – 15% **Testing set** – 15%

  This ensured that the model could learn effectively while also being evaluated on unseen data to measure generalization performance.

- ✓ **label encoding**, converting:
  "yes" → 1 "no" → 0

  This encoding allows the neural network to treat the target as a binary classification problem, enabling the model to output probabilities for tumor presence or absence.

  These preprocessing steps ensured that the dataset was clean, consistent, and properly formatted, effectively preparing it for training and evaluation. By encoding the target labels and applying necessary augmentations, the model could learn meaningful patterns for accurate brain tumor detection.

4.3 Technique

For this project, we utilized a **transfer learning approach** based on the ResNet50 architecture, a powerful convolutional neural network pretrained on the ImageNet dataset. Transfer learning allows leveraging previously learned features from large-scale datasets, enabling faster convergence and improved performance on limited medical imaging data.

The base ResNet50 model was loaded without its top classification layers (`include_top=False`), preserving the convolutional feature extractor while allowing us to add custom dense layers suited for binary classification of brain tumor presence.

Key aspects of the model architecture include:

- **Frozen Base Layers:** The pretrained ResNet50 layers were initially frozen to retain their learned filters and prevent overfitting during early training.
- **Global Average Pooling:** Applied after the convolutional base to reduce each feature map to a single value, drastically lowering the number of parameters before dense layers.
- **Fully Connected Layers:** A dense layer with 128 neurons and ReLU activation was added to learn task-specific features.
- **Output Layer:** A single neuron with sigmoid activation outputs the probability of tumor presence, enabling binary classification.

To improve model generalization, I applied data augmentation techniques such as rotation, shifts, and zooming through Keras' `ImageDataGenerator`, combined with the ResNet-specific preprocessing function to normalize inputs.

The model was compiled with the Adam optimizer and binary cross-entropy loss function, optimized for binary classification. Training was conducted over 10 epochs with validation to monitor performance.

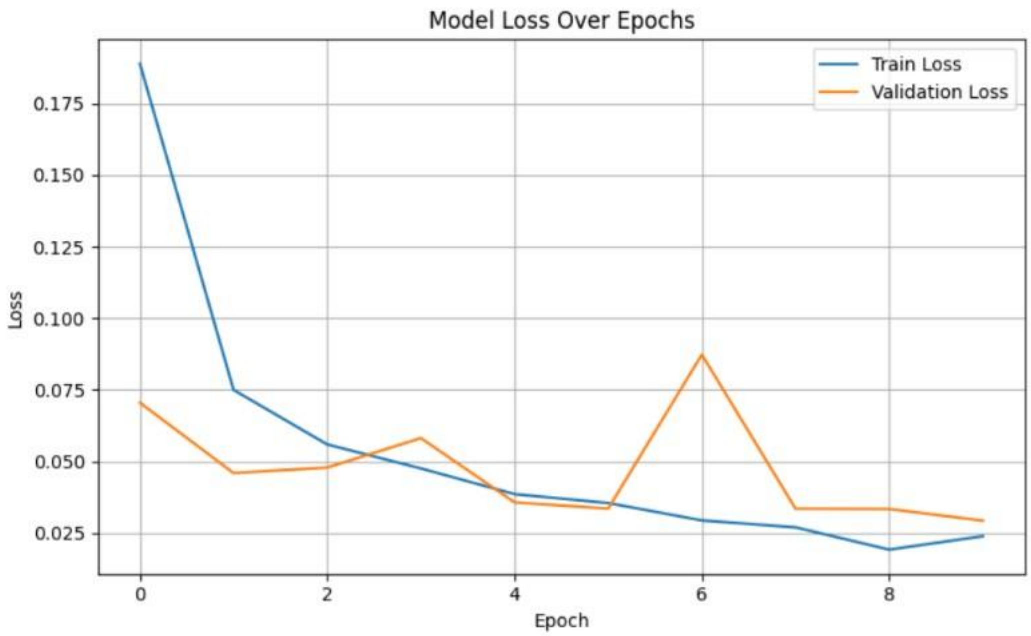
This approach successfully balances leveraging powerful pretrained features and task-specific learning, leading to robust brain tumor detection from MRI images.

4.4 Model Performance and Confusion Matrix

The performance of the model was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. In addition, training and validation metrics were tracked across 10 epochs to monitor the model's learning behavior and generalization ability.

Throughout the training process, the model demonstrated strong and stable learning on the training set. The training accuracy consistently improved, reaching **99.49%** by the final epoch, while training loss dropped from **0.3464** to **0.0190**.

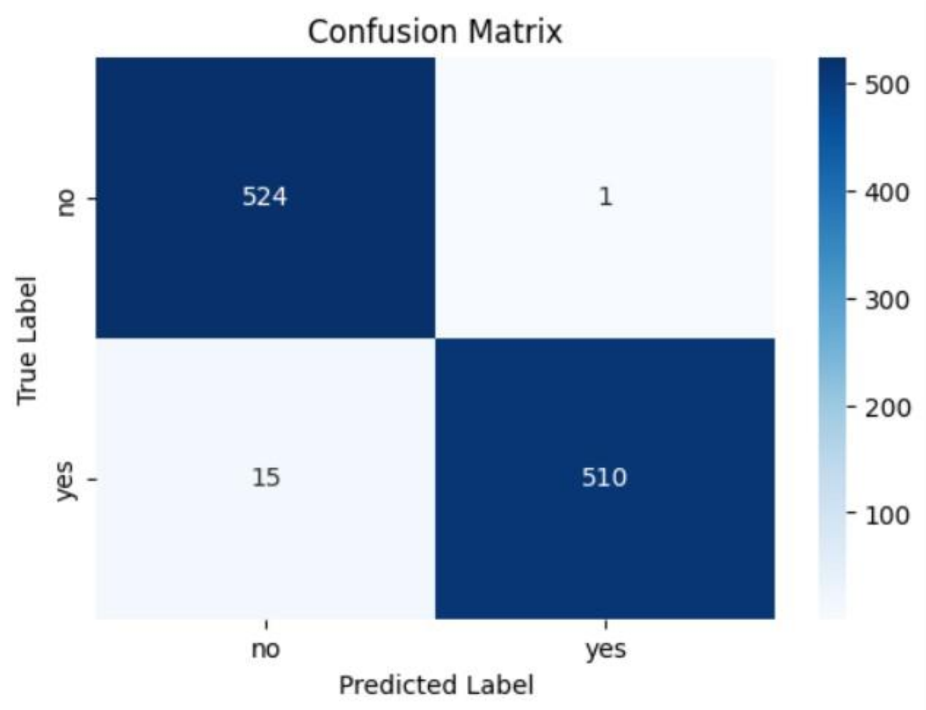
Validation accuracy also remained high, peaking at **99.52%**, and validation loss stayed low overall, though with slight fluctuations—indicating that the model generalizes well without significant overfitting.



This plot illustrates how the loss (error) decreased over time for both the training and validation sets. The training loss decreased smoothly and consistently, confirming that the model optimized well during training. The validation loss also decreased overall but showed minor increases in some epochs, such as epoch 7. These temporary increases are common and typically occur due to variability in unseen validation data. The gap between training and validation loss remained small, further confirming that the model is not overfitting and is able to generalize to new data effectively.

This plot shows how the model's accuracy evolved during the training process. The training accuracy steadily improved across epochs, reaching above 99% by the final epoch, which indicates the model effectively learned patterns from the data. The validation accuracy remained consistently high, with minor fluctuations. This reflects good generalization performance and suggests that the model did not overfit significantly. The small drop in validation accuracy in epoch 7 may be attributed to random variation in the validation set, but overall stability is observed.

Following this, I used a **confusion matrix** to analyze the model's performance on the test data by comparing the predicted labels against the true labels. The matrix below shows the number of correct and incorrect predictions for each class:



The confusion matrix above illustrates the model's classification performance across the two classes: **'no'** (no damage) and **'yes'** (damage). Out of 1,050 test samples, the model correctly predicted **524** out of 525 'no' instances and **510** out of 525 'yes' instances. There was **only 1 false positive** (predicting damage when there was none) and **15 false negatives** (failing to detect damage). These results indicate that the model is slightly more conservative in predicting damage but overall achieves a **high classification accuracy with minimal errors**, consistent with the performance metrics presented above.

To further evaluate classification performance, the final model was tested on a separate dataset, and the results are summarized in the following classification report:

	precision	recall	f1-score	support
no	0.97	1.00	0.98	525
yes	1.00	0.97	0.98	525

Overall, the model demonstrates excellent performance, achieving a high accuracy of **98.48%** on the test set. Both classes ("yes" and "no") are predicted with balanced precision, recall, and F1-scores, indicating that the model is not biased toward one class. The low number of misclassifications in the confusion matrix (only 16 out of 1050 samples) further supports its reliability. Additionally, the consistency between training and validation accuracy over epochs shows that the model has generalized well without significant overfitting. These results suggest that the model is robust and highly effective for the given classification task.

5. References

[1] Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., Pal, C., Jodoin, P.-M., & Larochelle, H. (2017). Brain Tumor Segmentation with Deep Neural Networks. *Medical Image Analysis*, 35, 18–31.

[6] Pereira, S., Pinto, A., Alves, V., & Silva, C. A. (2016). Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images. *IEEE Transactions on Medical Imaging*, 35(5), 1240–1251.